Digital City Inference and Generation

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Levels

- Level 0
  - LCZ and derivative work is doing great!
- Level 1
  - Start resolving individual buildings
  - Produce improve urban parameterization…
- Level 2
  - Develop novel and impact urban planning and design applications

Levels

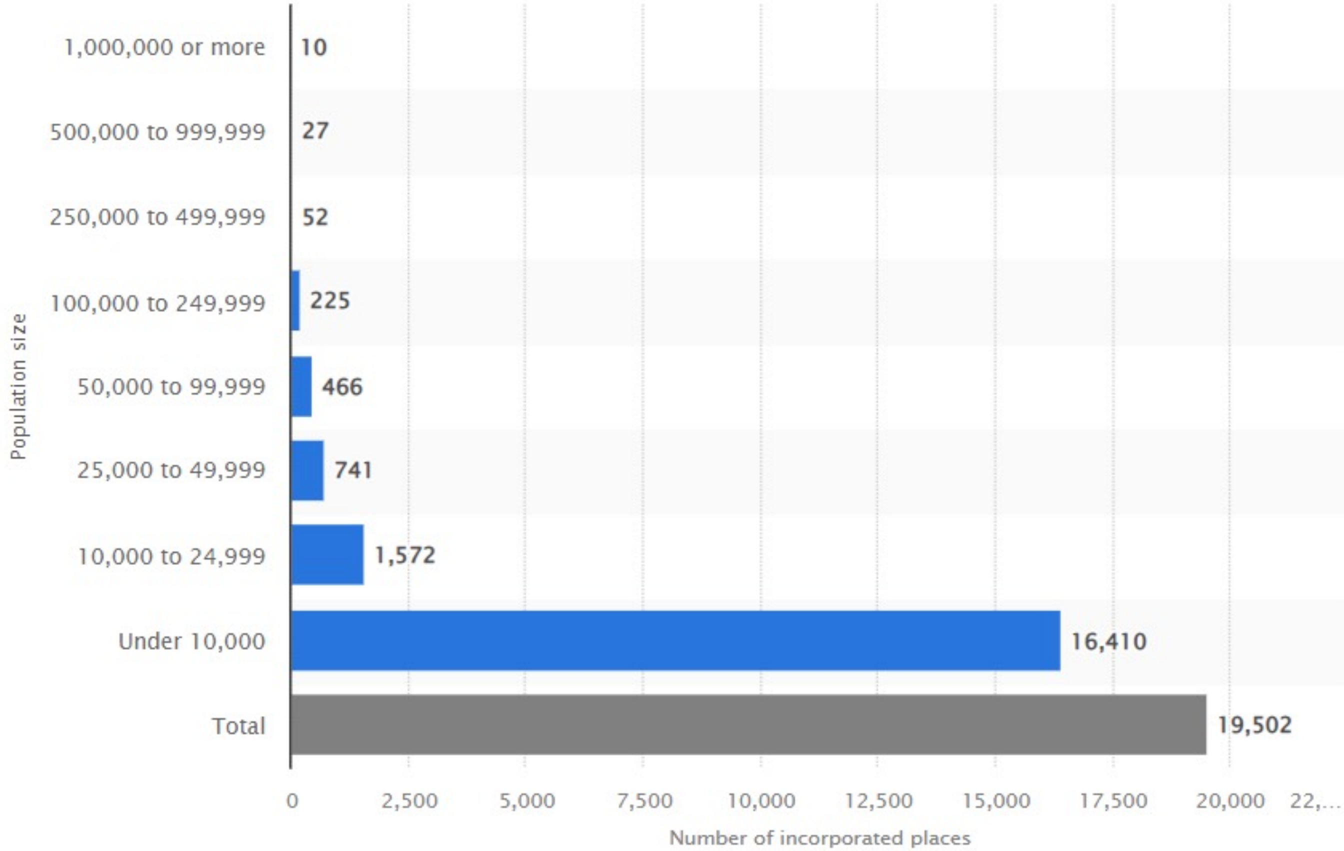
- Level 0
  - LCZ and derivative work is doing great!

- **Level 1**
  - **Start resolving individual buildings**
  - **Produce improve urban parameterization values…**

- Level 2
  - Develop novel and impact urban planning and design applications

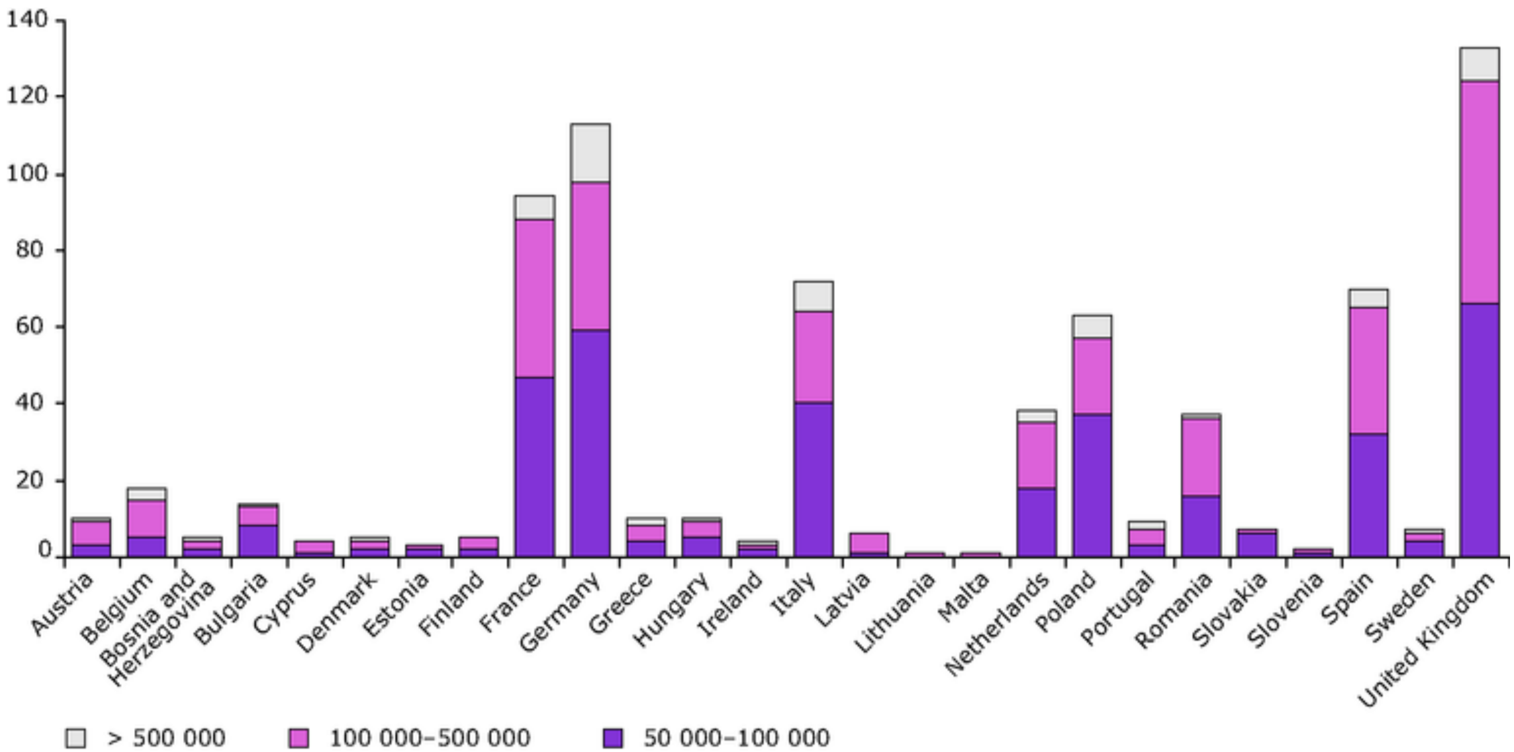
Cities

- Most people live in smaller cities
- US:



Cities

- Most people live in smaller cities
- Europe:



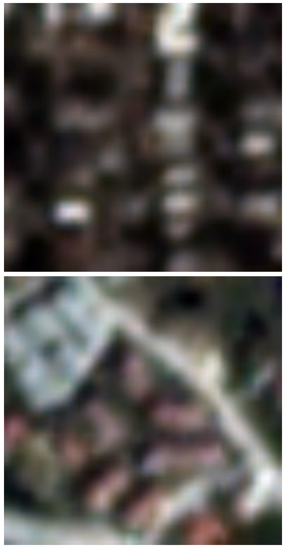
Problem: Missing Data

- >80% of the people living in cities are NOT in big metropolis
- Large metropolis are data rich but the cities where most people live are NOT data rich

Problem: Missing Data

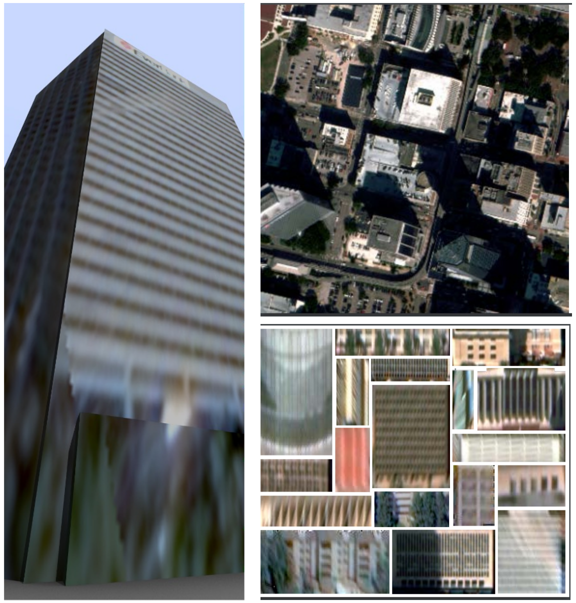
- Typical Data and Limitations

PlanetLabs



Limited details, missing data

Worldview

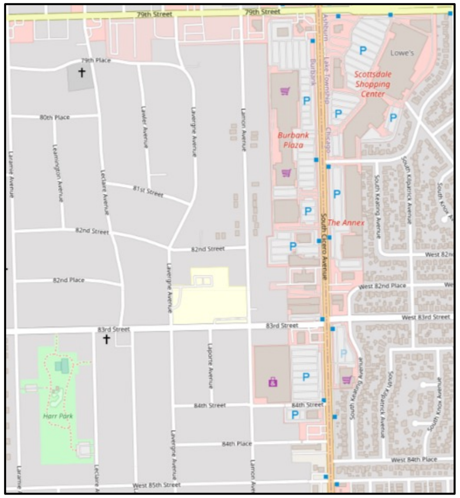


$$$, medium details, missing data

Aerial

High details, low coverage, missing data

OSM: crowd-sourced



High details, low coverage, missing data

(scarcity and missing data only exacerbated in small/med cities)

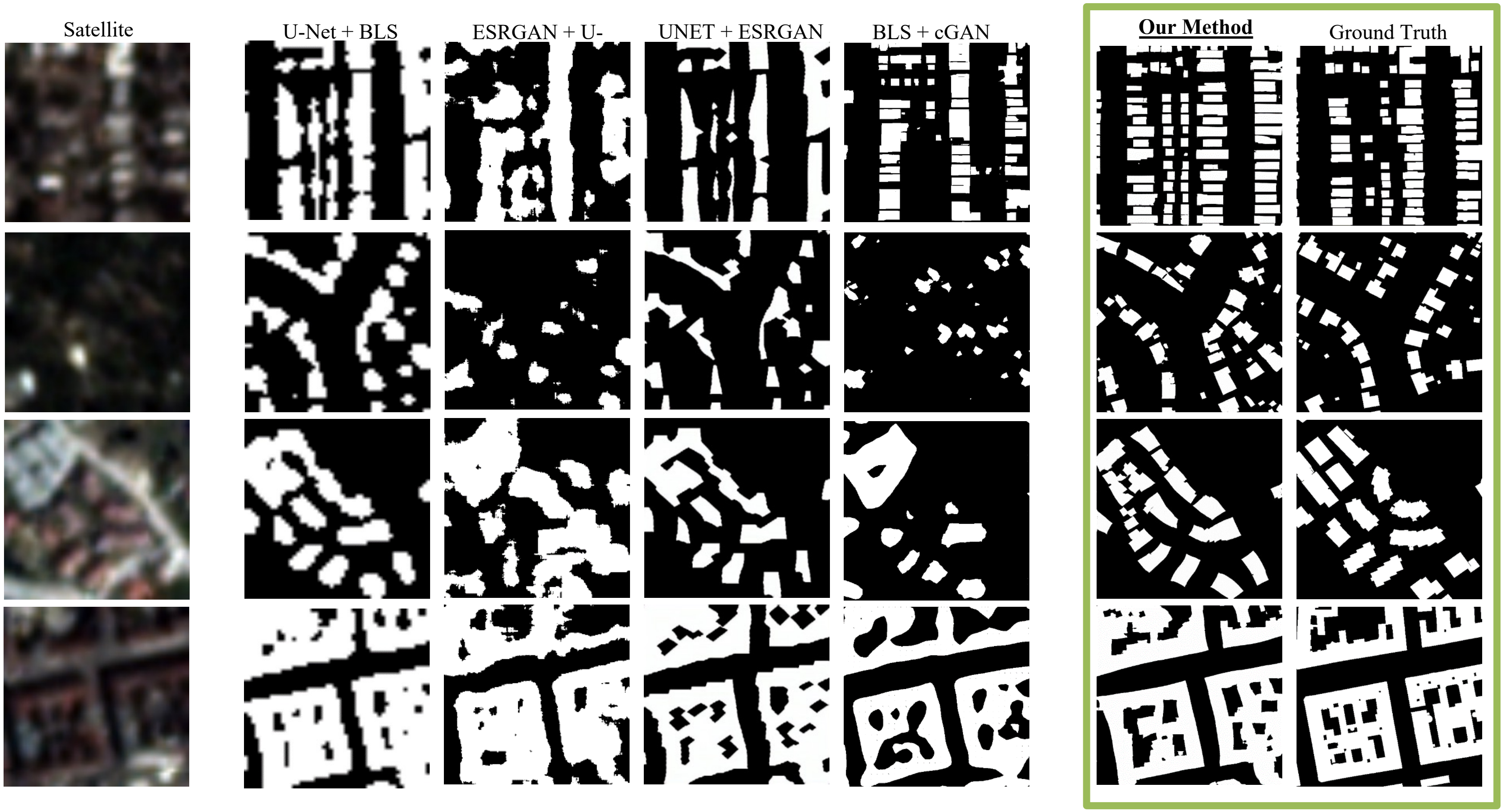
[He et al. 2022]

Solution: Digital Synthetic Cities

- Generate a “statistically similar” synthetic building and/or city
- Use whatever crowd-sourced and captured data is available (e.g., OSM, satellite-if-any)
  - It provides data that is incomplete but highly varied
- Then a deep generative network can learn the generalized “style” (i.e., distribution) from a noised large-scale dataset.
  - Does not produce a perfect reconstruction, but is of a similar distribution and thus suitable for many types of simulations
  - Output is fully synthetic and annotated so numerous what-if scenarios can easily be performed
    - i.e., “**see more than we can see**”

Solution (1 of N):
Capture a subset and generate

- Satellite images: generate hi-res segmentation from low-res



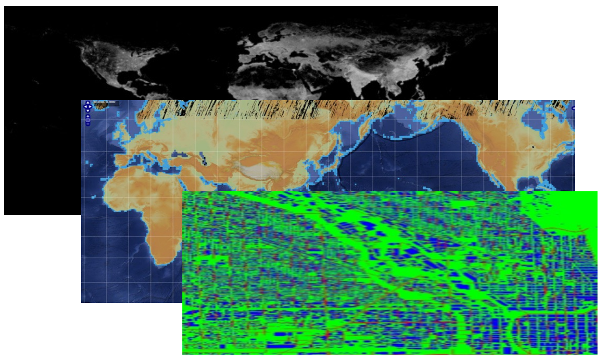
5-50% better than prior methods

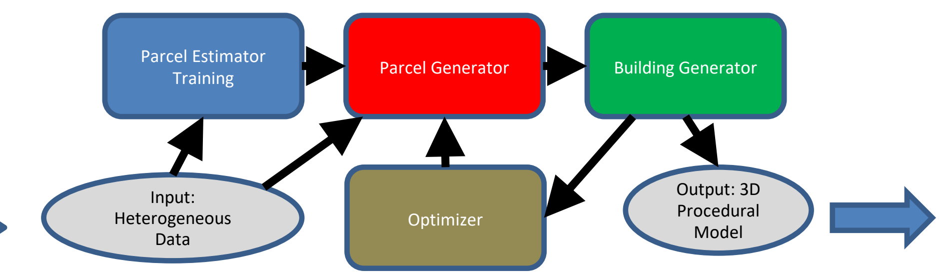
[He et al. 2023]

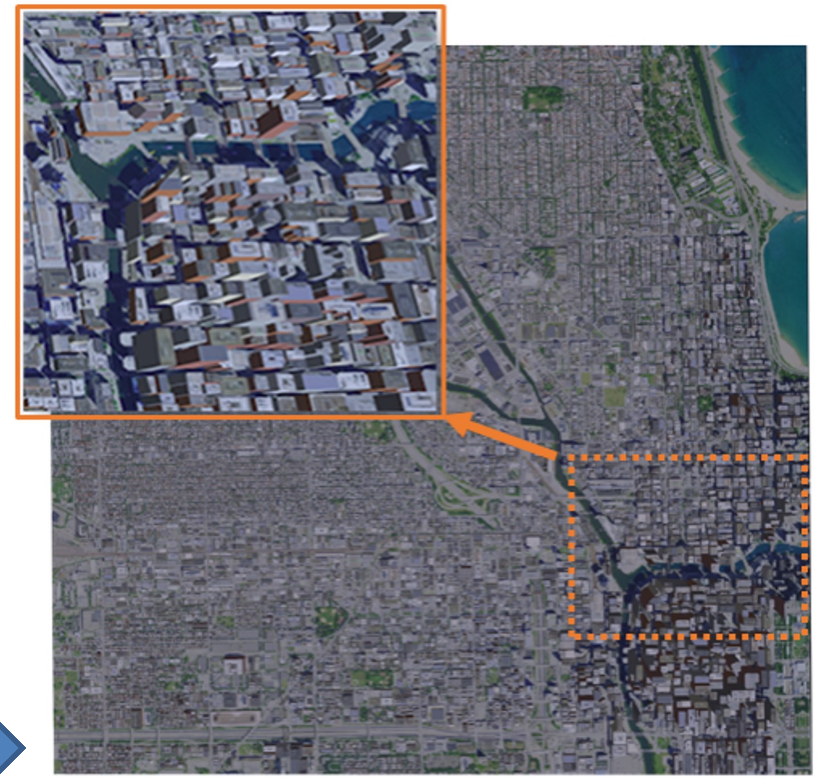
Solution (2 of N): Capture a subset and generate

- Satellite images: generate cities from low-res

LandScan, JAXA, Segmentation



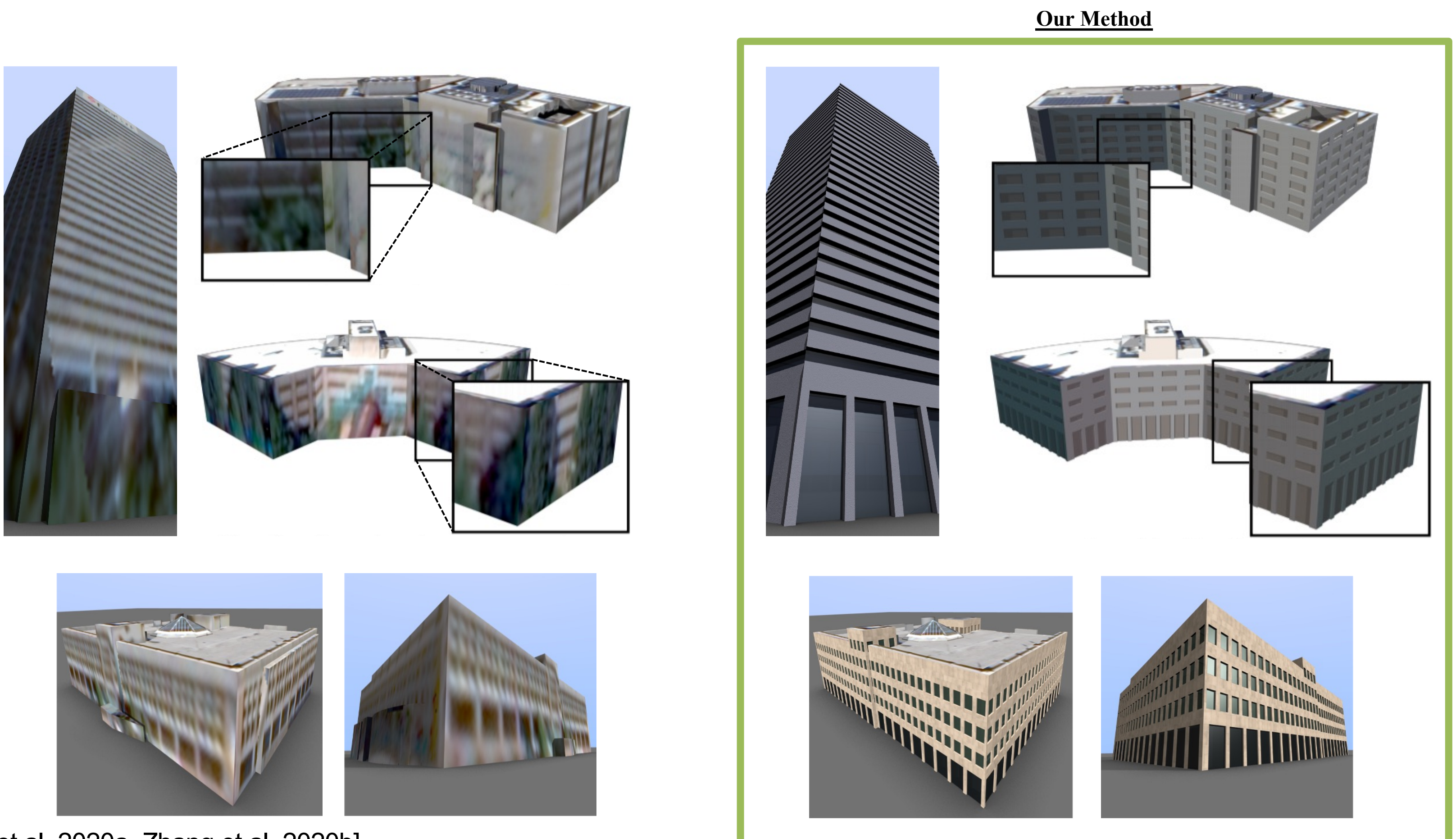




[Zhang et al. 2021]

Solution (3 of N):
Capture subset and generate

- Produce procedural facades from partial data



[Zhang et al. 2020a, Zhang et al. 2020b]

Solution (4 of N): Capture subset and generate

- From one ground image, produce entire bldg

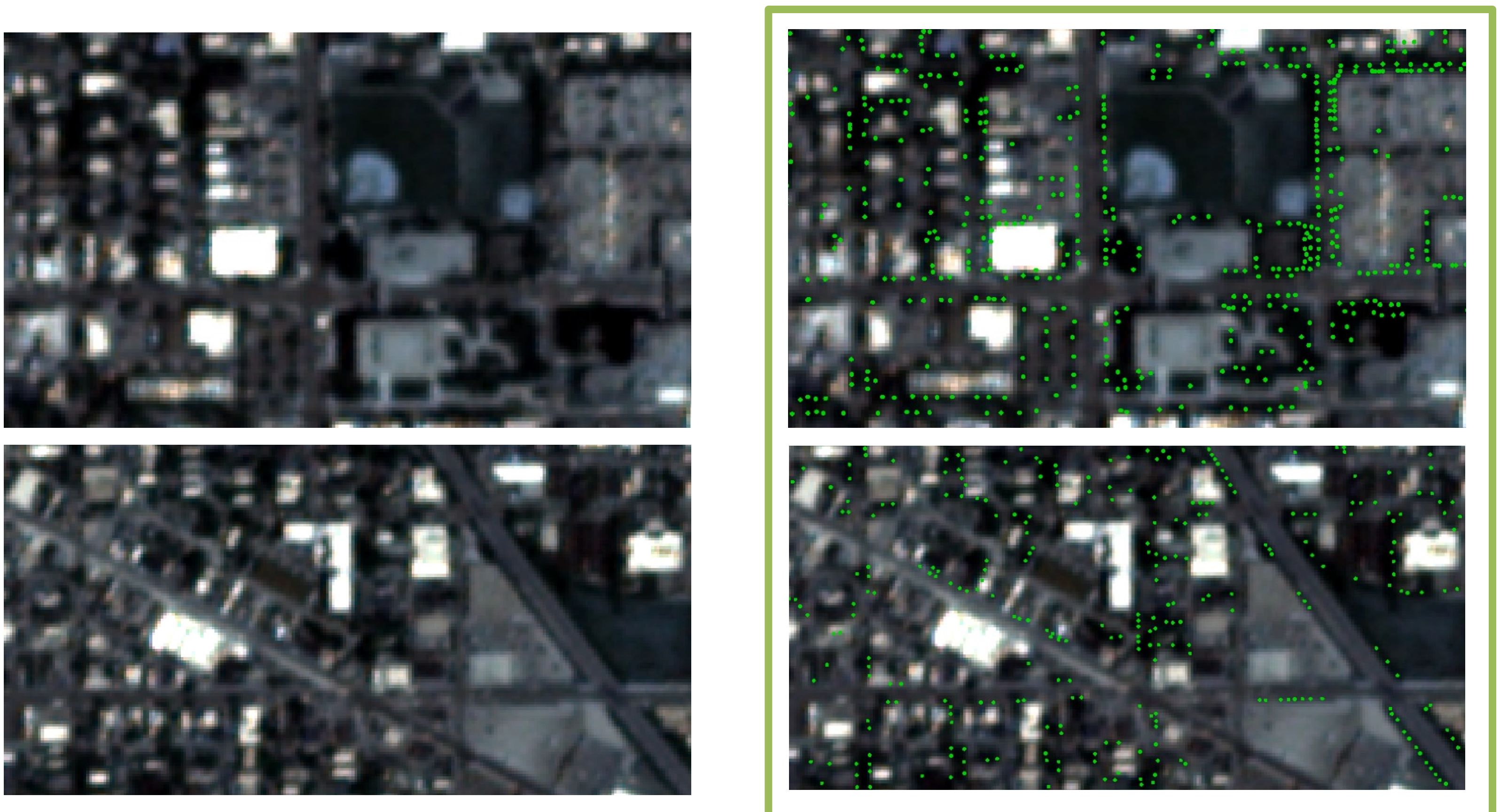
Our Method

[Nishida et al. 2018, Bhatt et al. 2020]

Solution (5 of N):
Capture subset and generate

- Use spatio-temporal satellite images to localize individual trees

Our Method



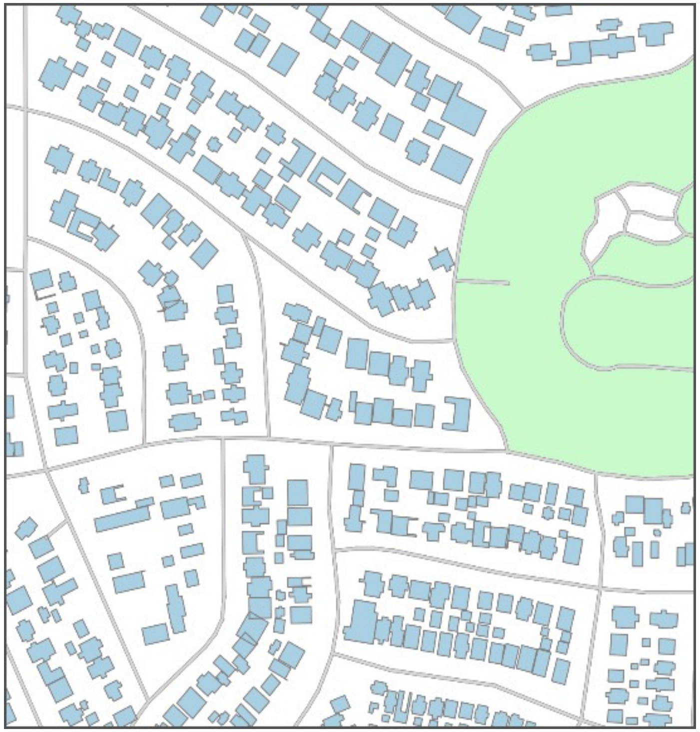
Accuracies of 87-97%

[Firoze et al. 2022]

Solution (6 of N): Capture subset and generate

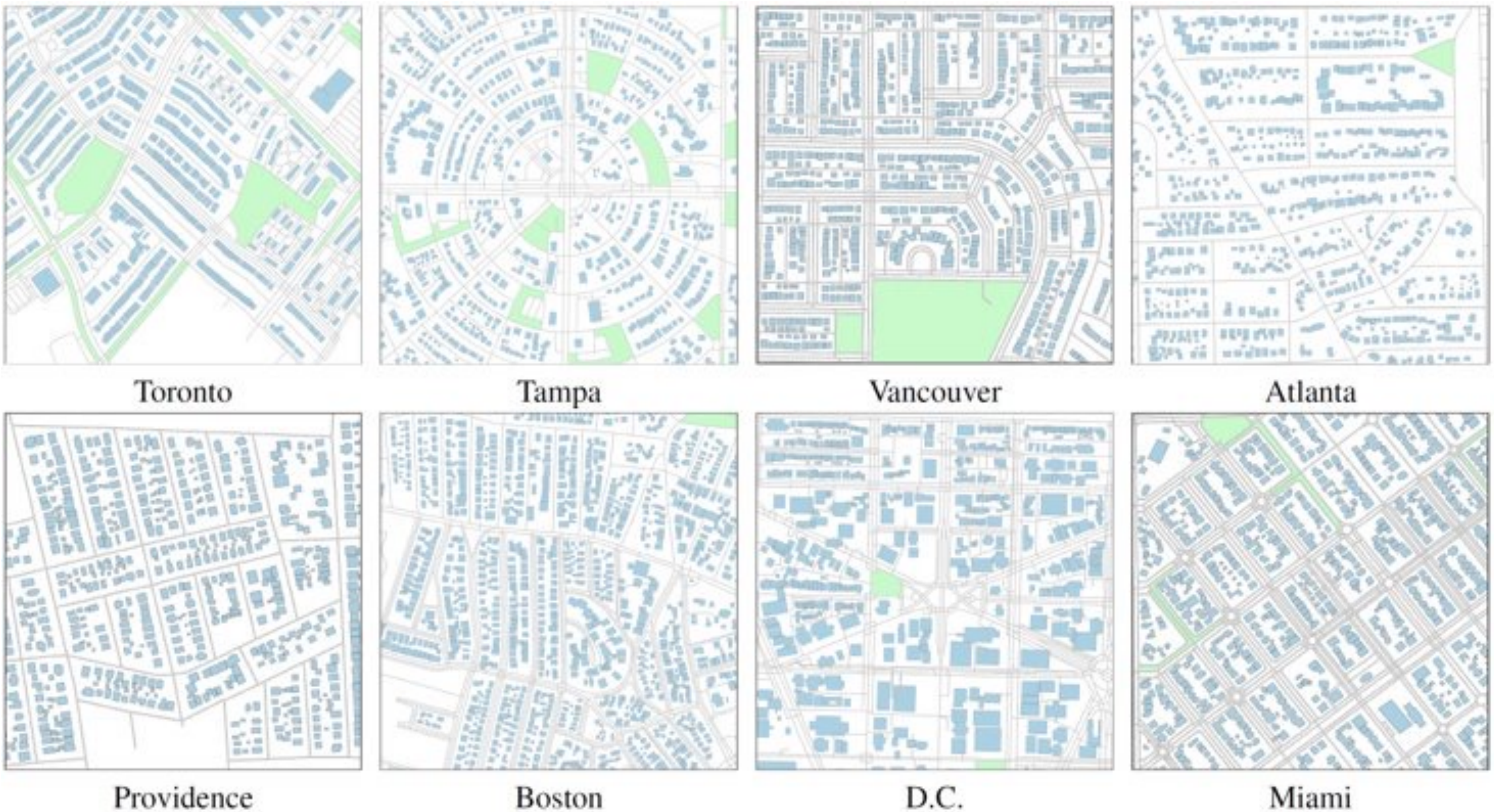
- Generate city layouts, then compute UCPs

Input: Roads+Priors



Output: Building Mass

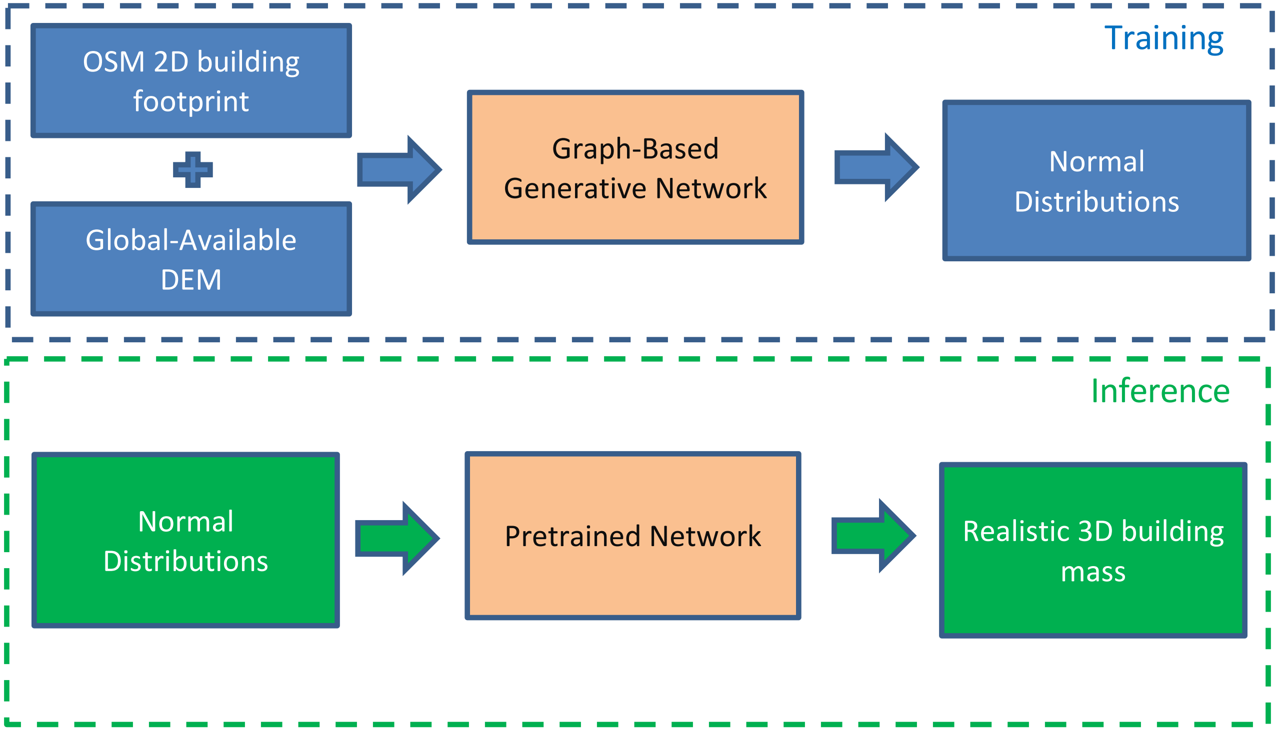
Deep Generative Layout Generation



Deep Generative Layout Generation

- We trained a generative network based on large-scale open resource dataset. The network is trained to represent all possible urban layout styles into a series of normal distributions.

- The well-pretrained model can synthetically generate realistic city blocks from normal distributions and marginal normal distributions indicated by user priors.



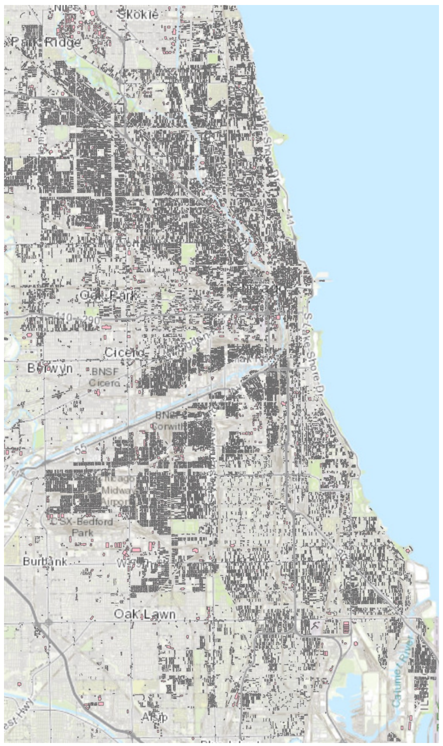
Deep Generative Layout Generation

- Current status
  - Tested/trained for 28 North American cities
    - Height data is also produced (Austin collaboration)
  - 100k city blocks
  - 2M buildings

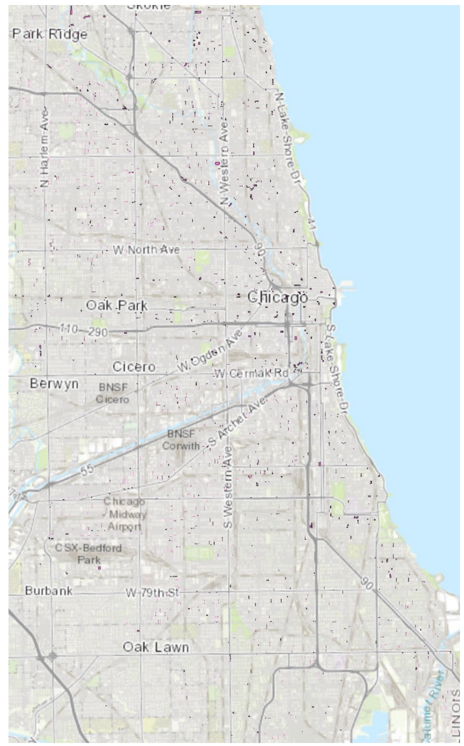
Experiment: Comparison

Experiment: Comparison

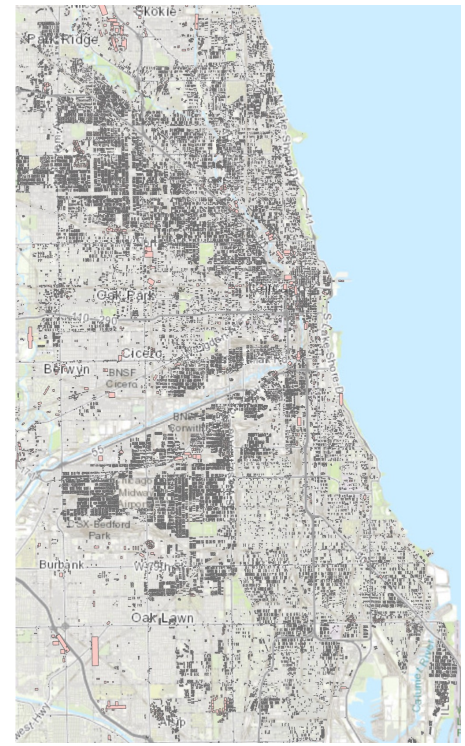
Experiment: Generate Chicago from 5% data



OSM shapefile



Only use x% (5% etc.)

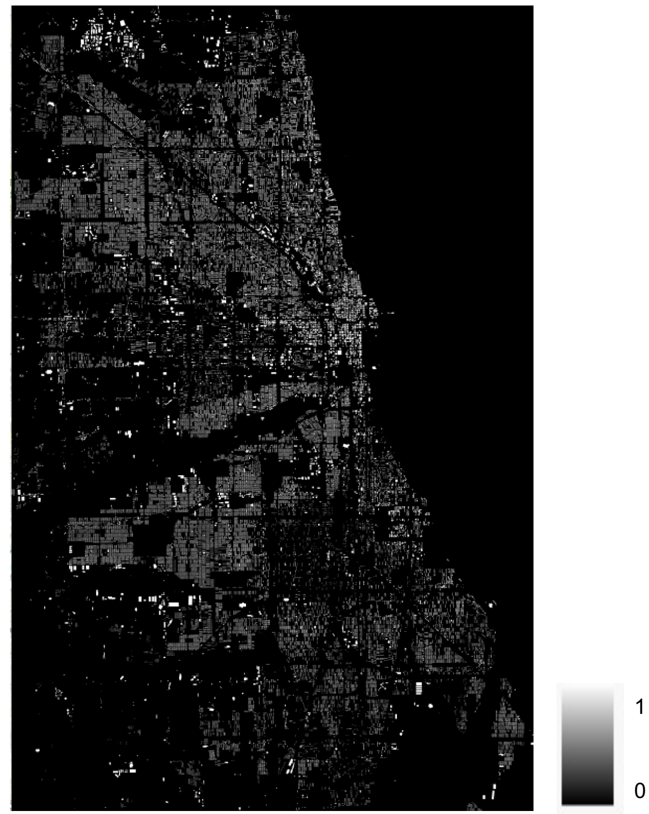


Generate entire city

Experiment: Generate Chicago from 5% data

Plan area ratio

Synthetic Generation

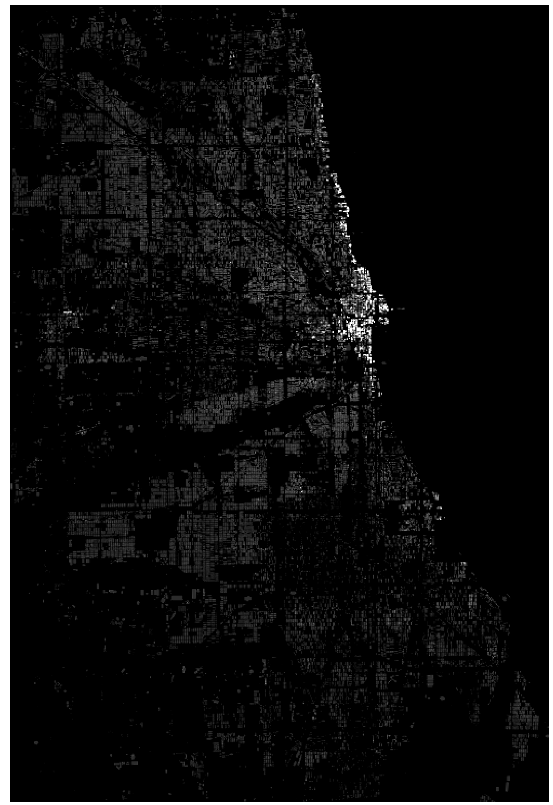


Ground Truth from OSM

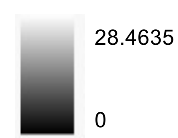
Experiment: Generate Chicago from 5% data

Building surface to plan area ratio

Synthetic Generation

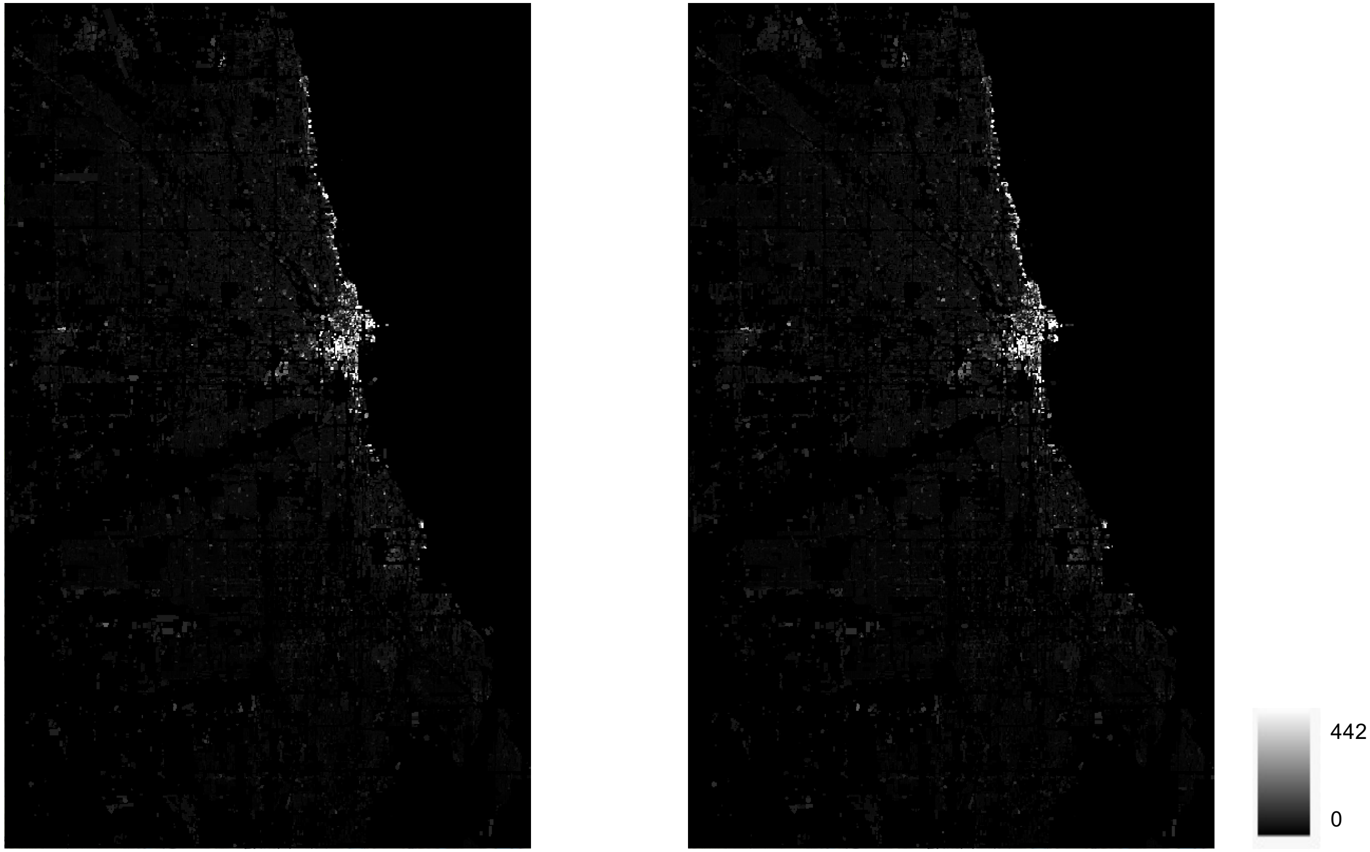


Ground Truth from OSM



Experiment: Generate Chicago from 5% data

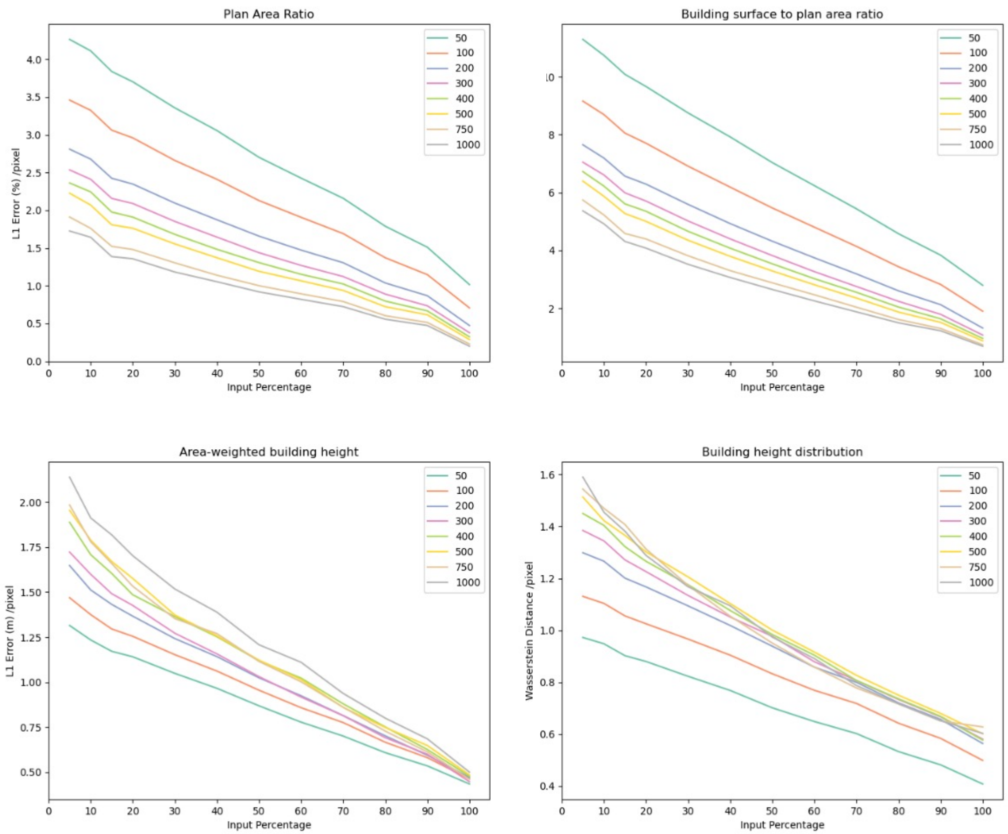
Area-weighted building height



Synthetic Generation

Ground Truth from OSM

L1 error using 5-100% of data



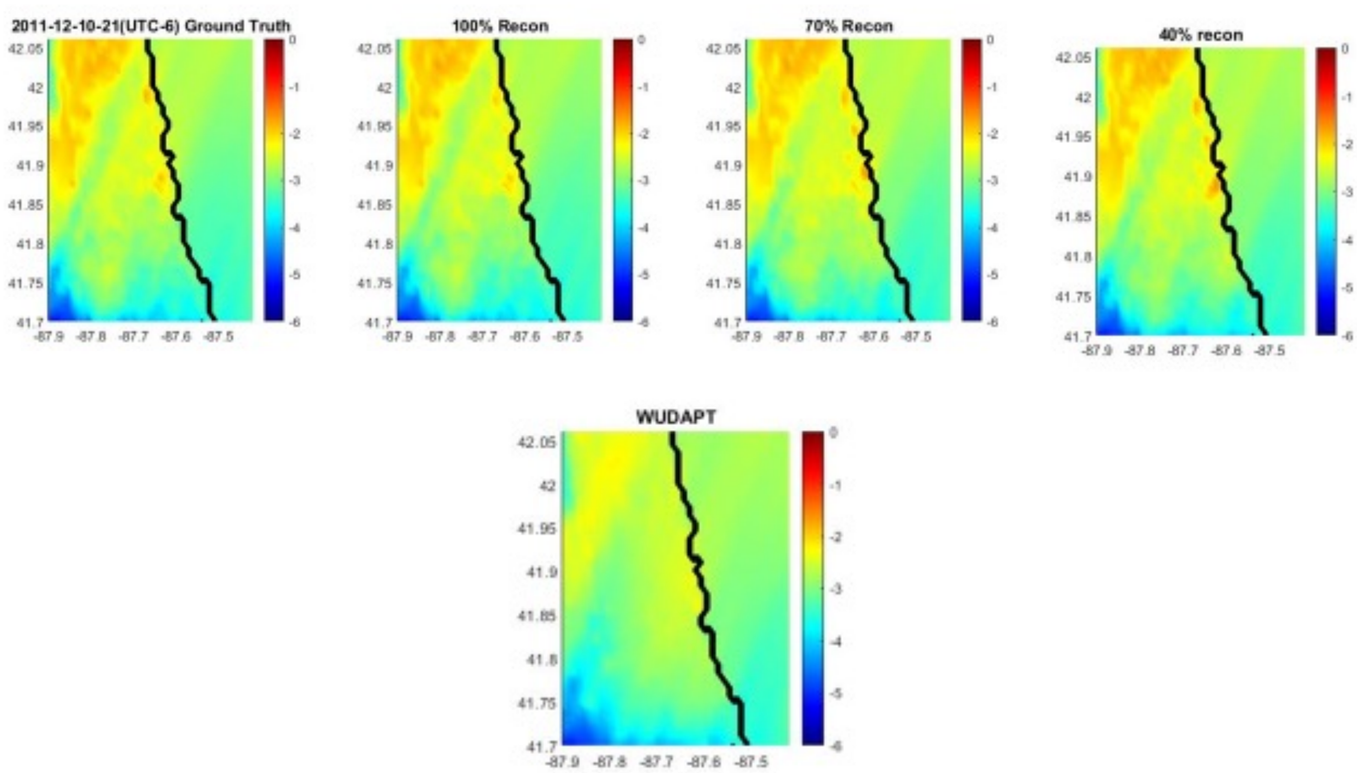
- With only 5% input, we can generate the entire city in the accuracy of:
  - Plan area ratio: L1 error < 2m per pixel
  - Building surface to plan area ratio: L1 error < 11% per pixel
  - Area-weighted building height: L1 error < 2.1 m per pixel
  - Building height distribution: W-distance < 1.6 per pixel

L2: Applications

- WRF-Urban
  - As one application, we have run WRF-Urban forecasts and what-ifs for several cities:
    - Chicago, Indianapolis, Austin
- Flooding
- Vehicular Traffic

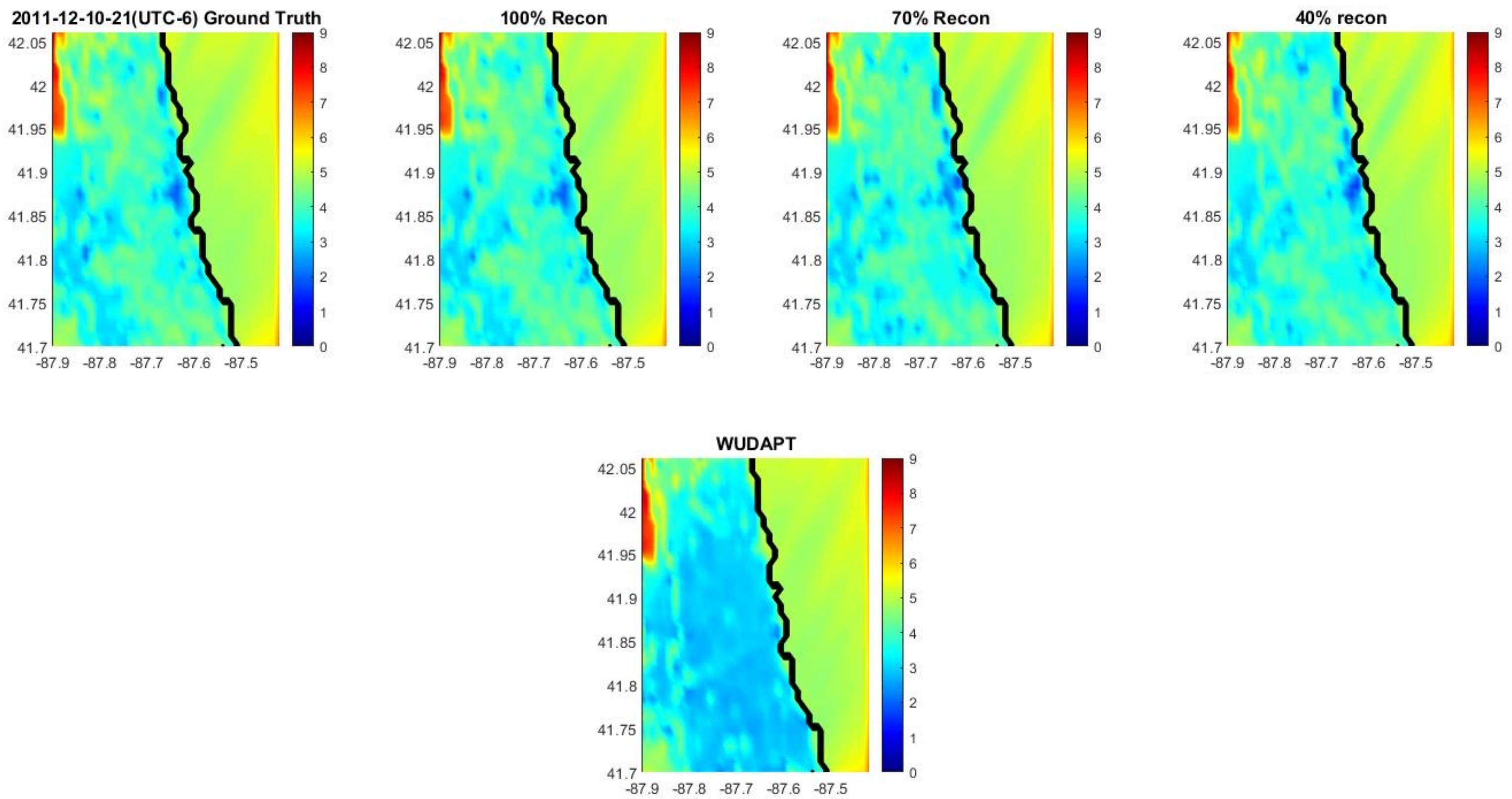
WRF-Urban Simulations

Surface Temperature

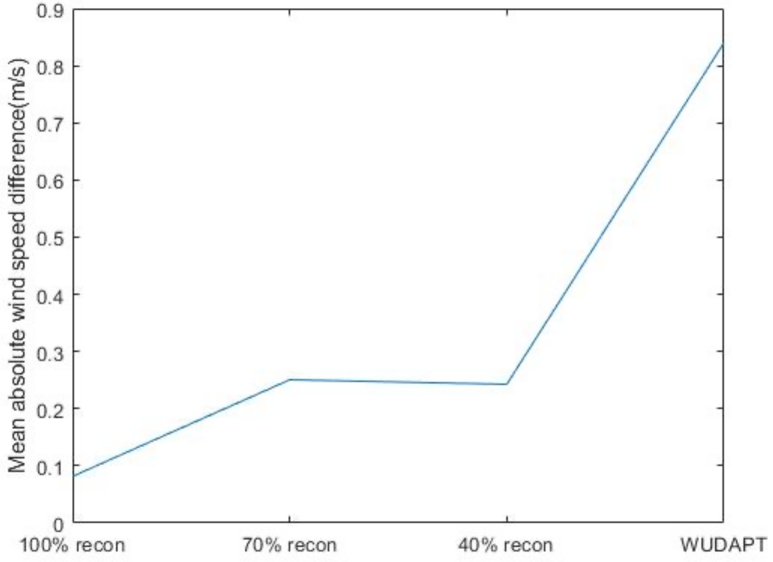


WRF-Urban Simulations

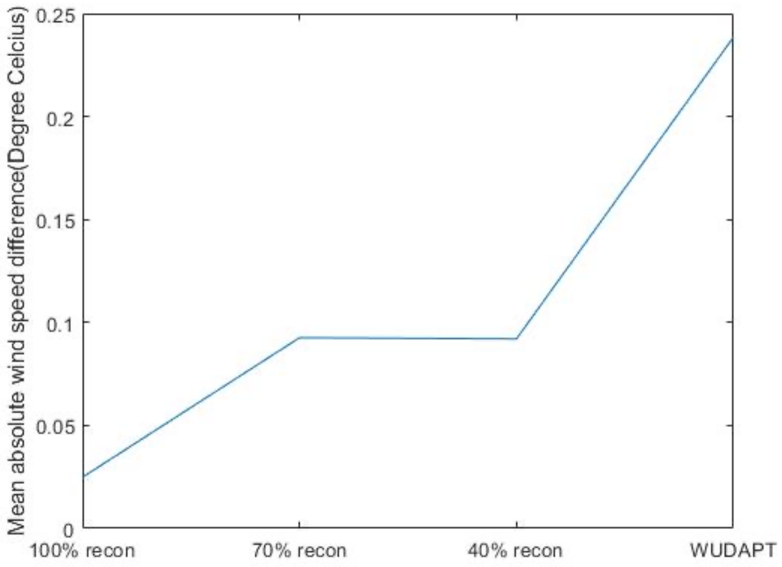
Wind Speed



WRF-Urban Simulations



Wind speed (m/s)



Temperature (Degree Celsius)

Other Applications: Urban Cloud Control

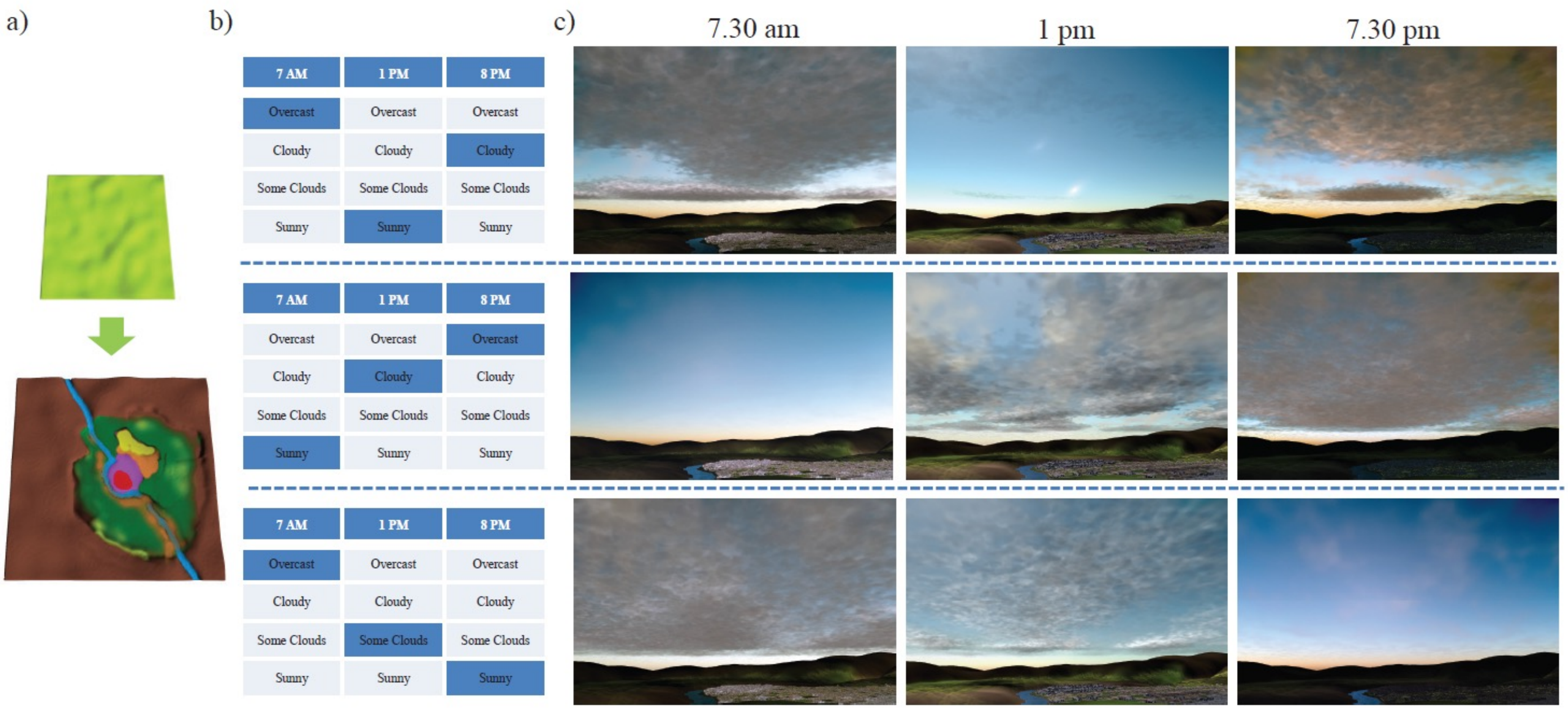


Fig. 10. **Inverse Cloud Design.** Three examples of cloud design. a) The user interactively draws a land use distribution; b) the user selects three different high-level behaviors of the weather; c) the system finds such weather and the weather sequence is visualized.

[Garcia-Dorado et al. 2017]

Other Applications: Temperature Mitigation

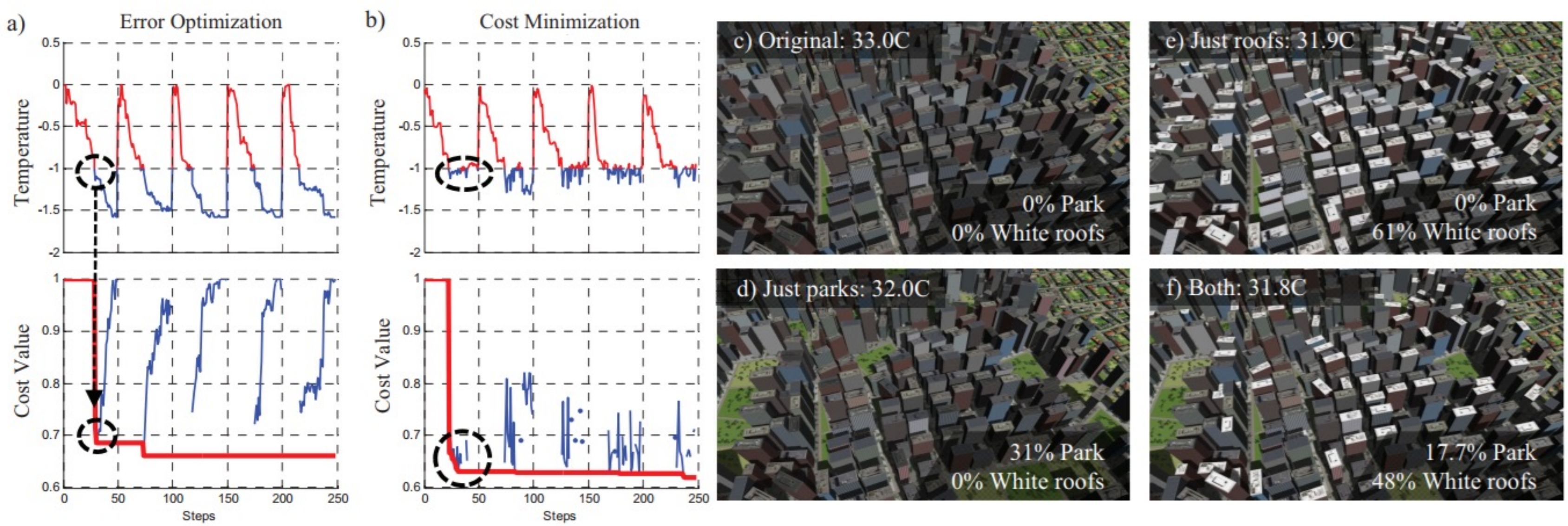
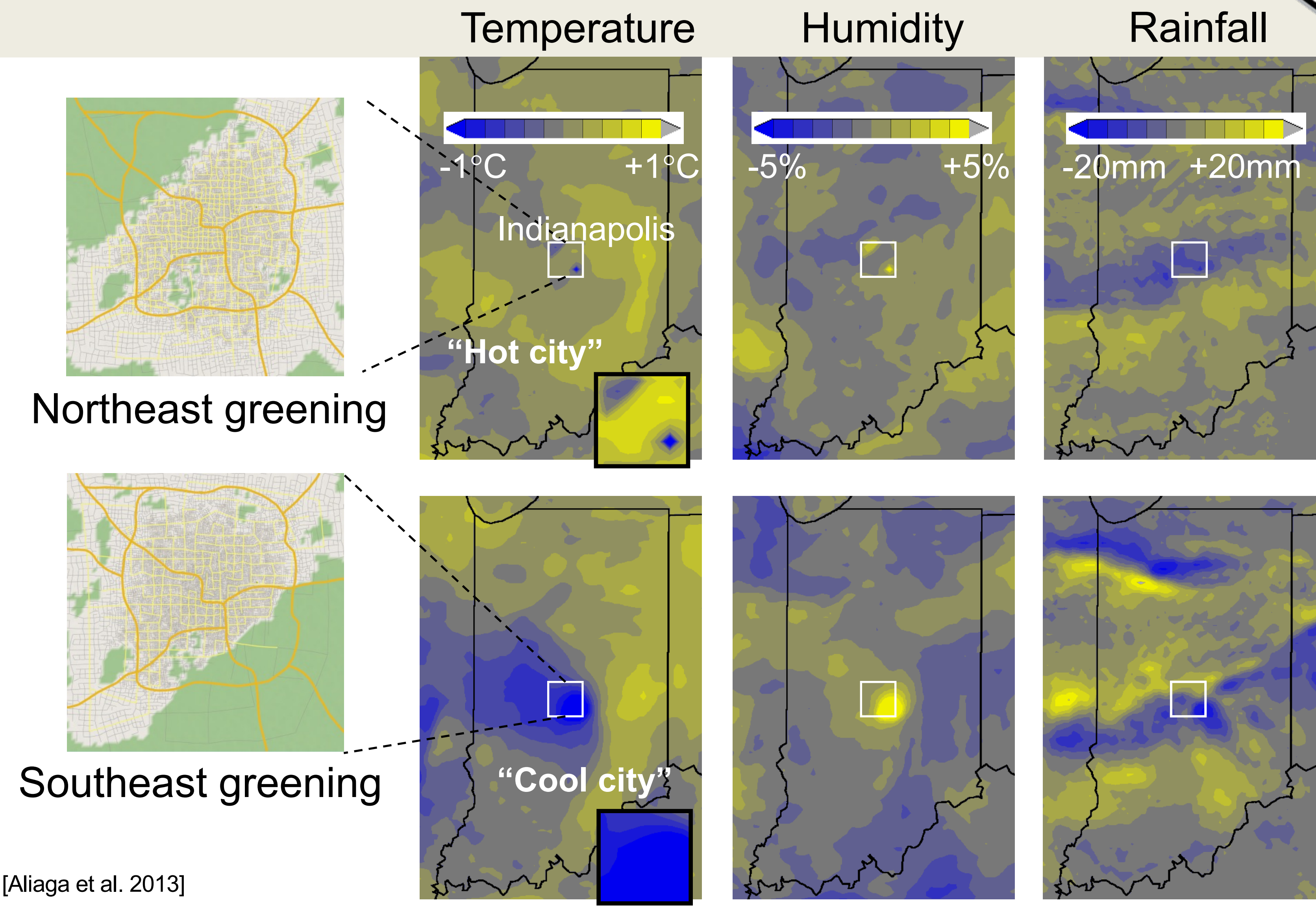


Fig. 12. **Inverse Temperature Design.** a-b) We show the behavior of the optimization for the solution e) of this figure: a) if our error optimization mode is used (i.e., optimize the temperature); b) if we use our cost minimization mode (i.e., temperature and cost optimization); c) the original model; d) altered model that achieves one degree reduction by introducing more parks; e) alternative model that achieves the same goal but uses white roofs to increase albedo; and f) a solution with both parks and white roofs (note the reduction in both).

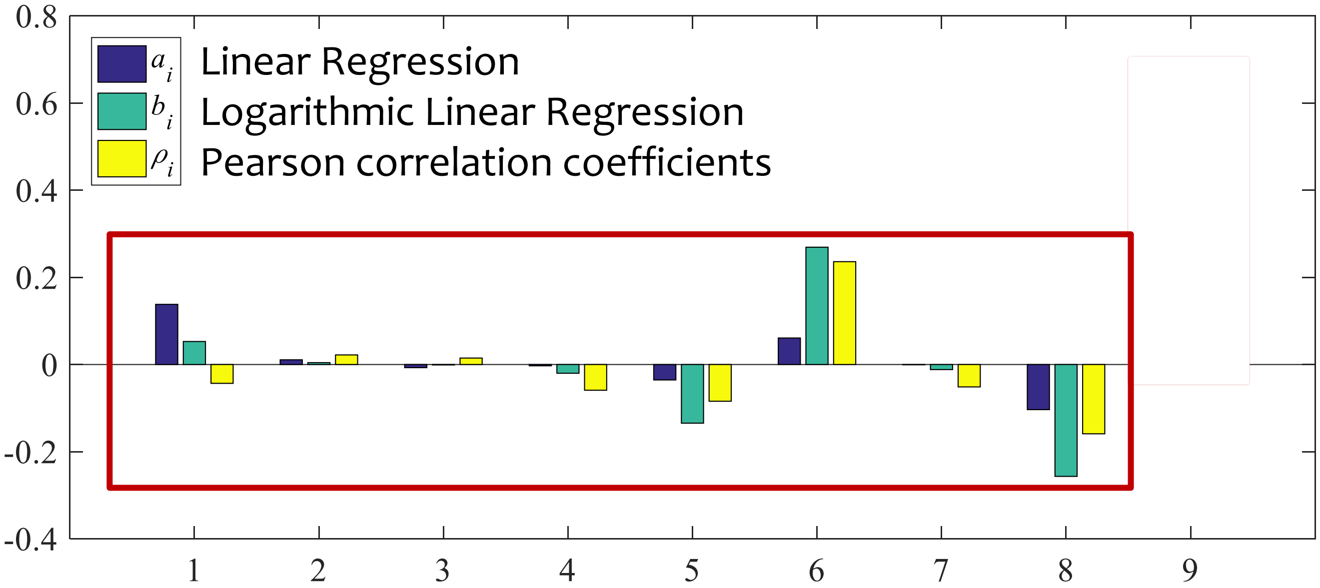
[Garcia-Dorado et al. 2017, Patel 2022]

Other Applications: Urban Greening



[Aliaga et al. 2013]

Other Applications: Urban Flooding



x_1: Average street length
x_2: Street orientation
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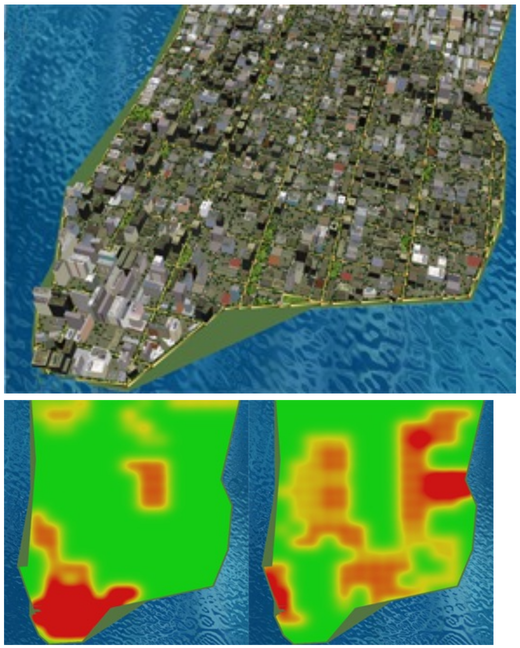
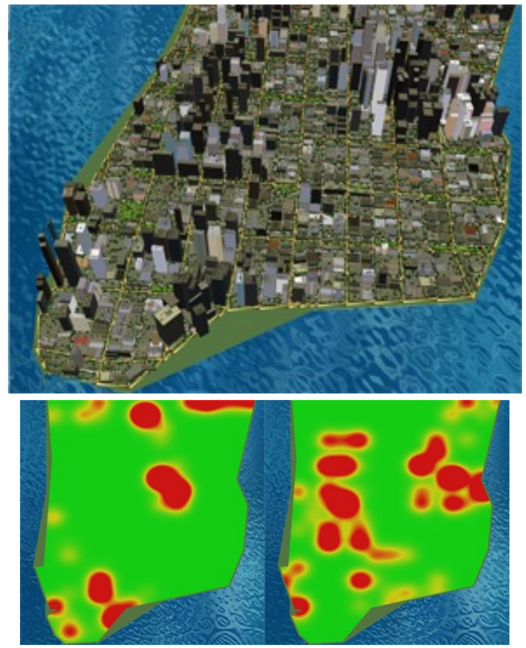
x_8: Building side setback
x_9: Building coverage

Other Applications: Urban Traffic

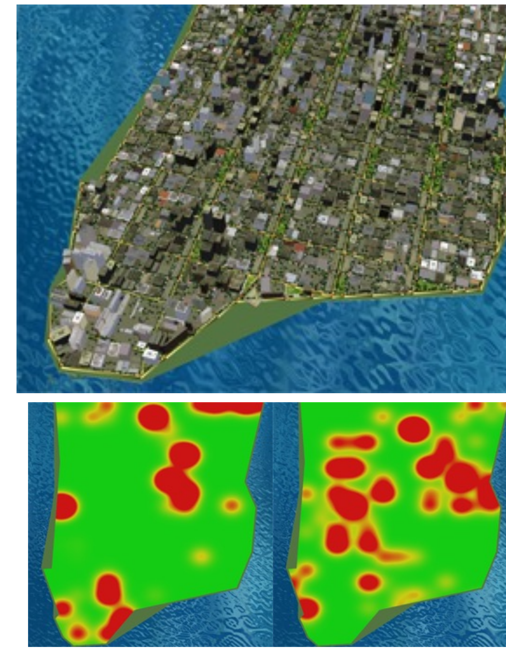
Solutions:



Travel Time: 50 min
CO: 980gr
52 Lanes



Travel Time: 40 min
CO: 622gr
16% Jobs
31% People
34 Lanes



Travel Time: 30 min
CO: 484gr
29% Jobs
44% People
61 Lanes

Short Term Next Steps

- Target: all US cities with >100k people
  - About 320 cities
  - About 80,000 sq km
- Part A: Generate tree count/location for all
  - Needs 1M sq km of satellite
  - Suitable for ecosystem services and urban planning
  - Team formed; project underway…
- Part B: Generate layout (and UCP) for all
  - Suitable for urban planning
  - Team being formed…

Who funds this multi-disciplinary work?

NSF

IARPA

USDA

Adobe

INTERNET 2

Google

Metropolitan Transportation Commission

It is not just us…

- **Co-Investigators [co-Is on grants and/or co-authors on pubs]**: Bedrich Benes (Purdue), Jason Ching (UNC), Songlin Fei (Purdue), Avi Kak (Purdue), Rajesh Kalyanam (Purdue), Ian Lindsay (Purdue), Gerald Mills (UC Dublin), Soraia Musse (PUCRS), Jennifer Neville (Purdue), Dev Niyogi (UT Austin), Manuel Oliveira (UFRGS), Nicholas Rauh (Purdue) Holly Rushmeier (Yale), Jacques Teller (U. Liege), Satish Ukkusuri (Purdue), Parker VanValkenburgh (Brown), Gunder Varinlioglu (MSFAU), Paul Waddell (UC Berkeley), Steve Wernke (Vanderbilt)

- **Graduate Students [underlined are my advisee's]**: Michel Abdul, <u>Daniel Bekins</u>, Sai Bhalachandran, <u>M. Bhatt</u>, <u>Ilke Demir</u>, <u>Ignacio Garcia-Dorado</u>, <u>Adnan Firoze</u>, <u>Liu He</u>, Ming Lei, <u>Tharindu Mathew</u>, <u>Chris May</u>, Ahmed Mustafa, <u>Gen Nishida</u>, Pratiman Patel, Paul Rosen, Paul Schmid, <u>A. Shehata</u>, Anamika Shreevastava, <u>Carlos Vanegas</u>, Innfarn Yoo, <u>Yi Xu</u>, <u>Zixun Yu</u>, <u>Xiaowei Zhang</u> (*and 5 more*)

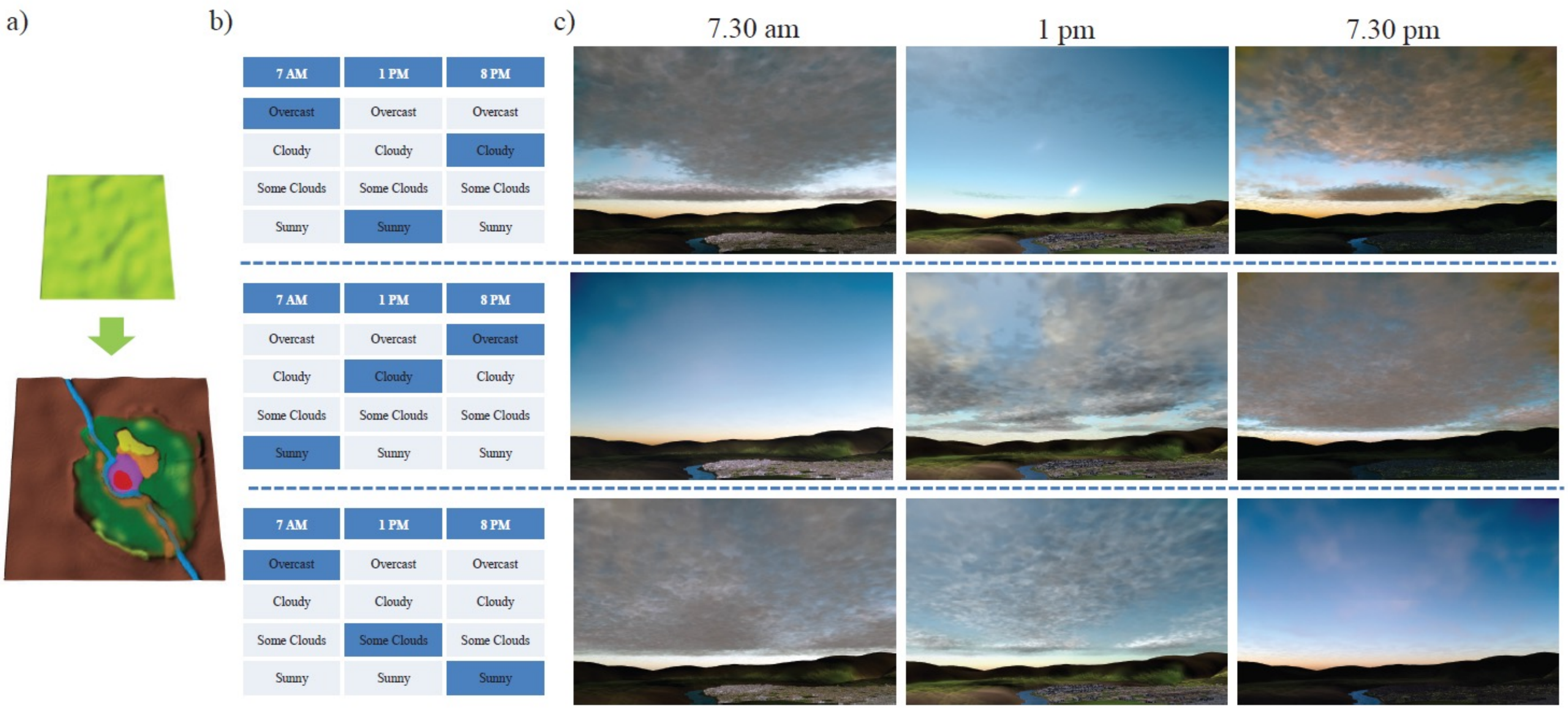
- **Undergraduate Students [produced papers or software kits]**: Andy Feldcamp, Hareesh Gali, Aahash Ganga, Jerry Hsu, Robert Insley, Philip Jarvis, Yeong-Ouk Kim, Aaron Link (*and 15 more*) www.cs.purdue.edu/homes/aliaga

Please see papers for more details!

(or ask us)

Questions?

Application: Urban Cloud Control



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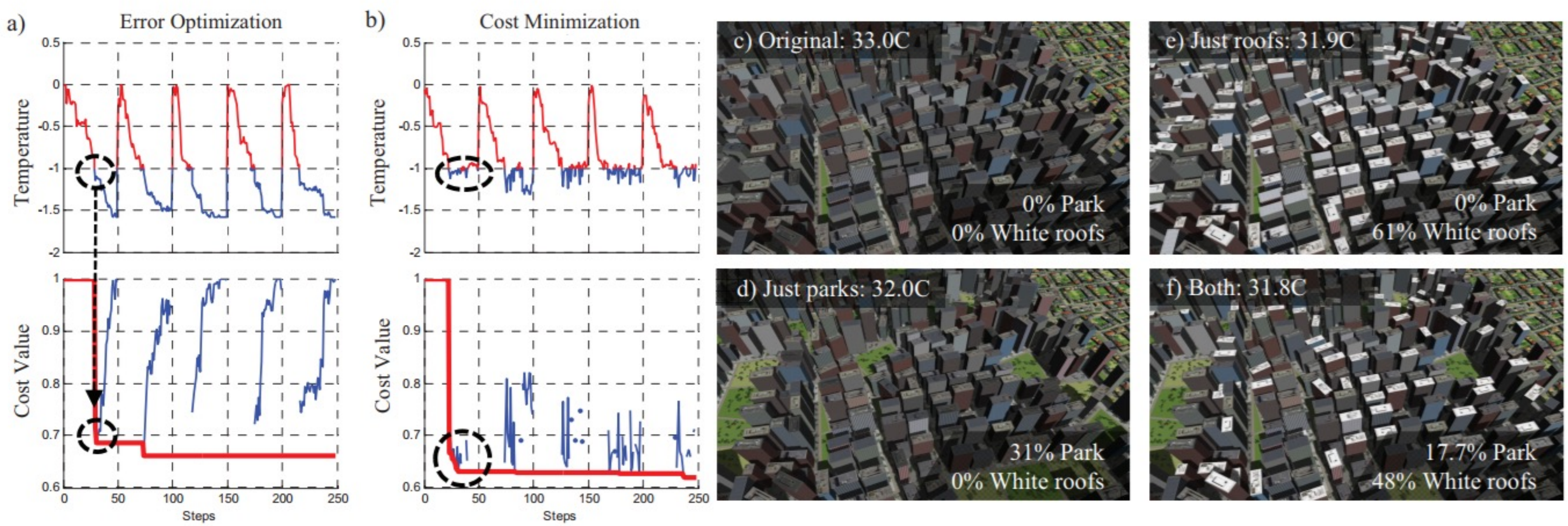
Application: Urban Temperature



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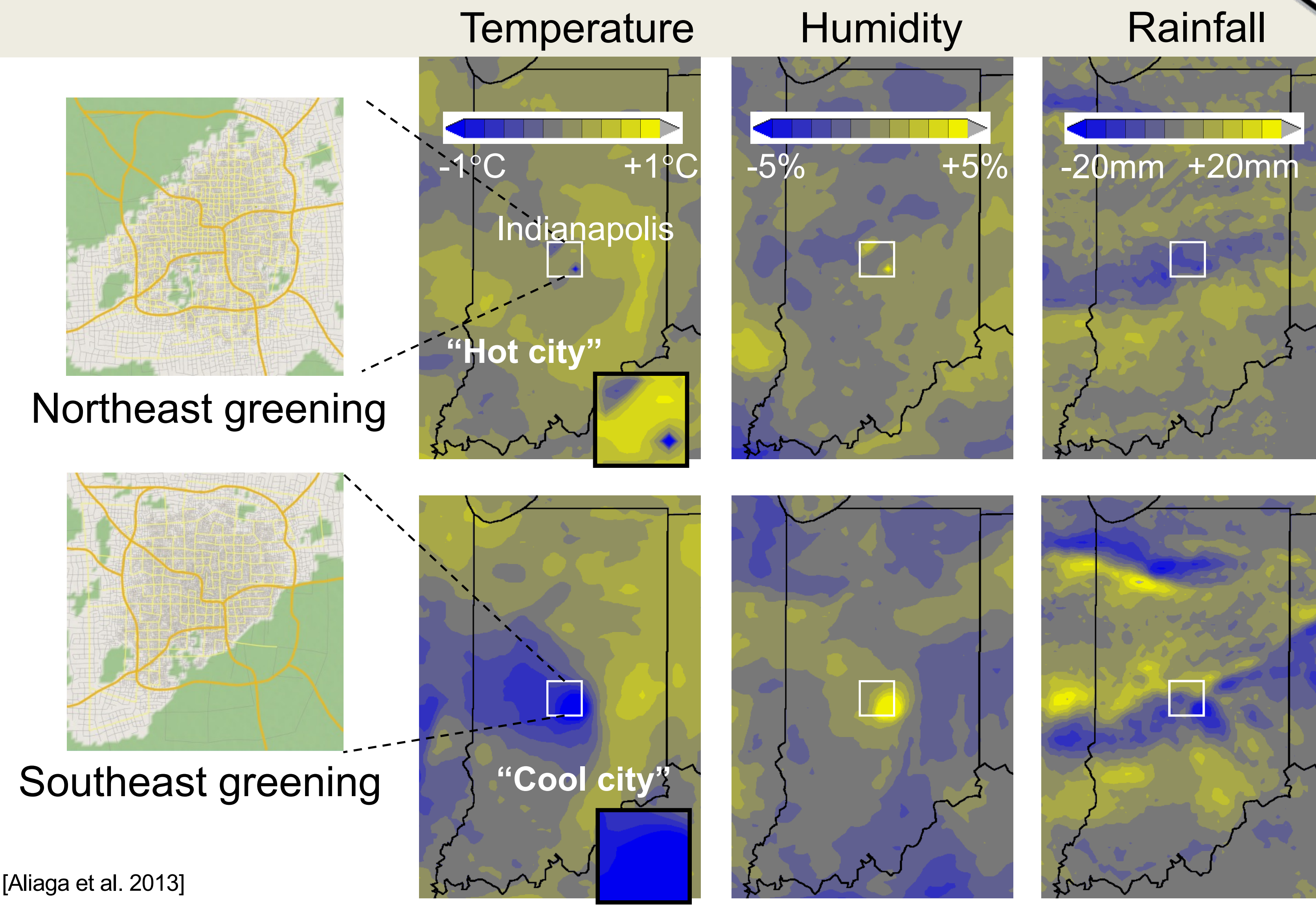

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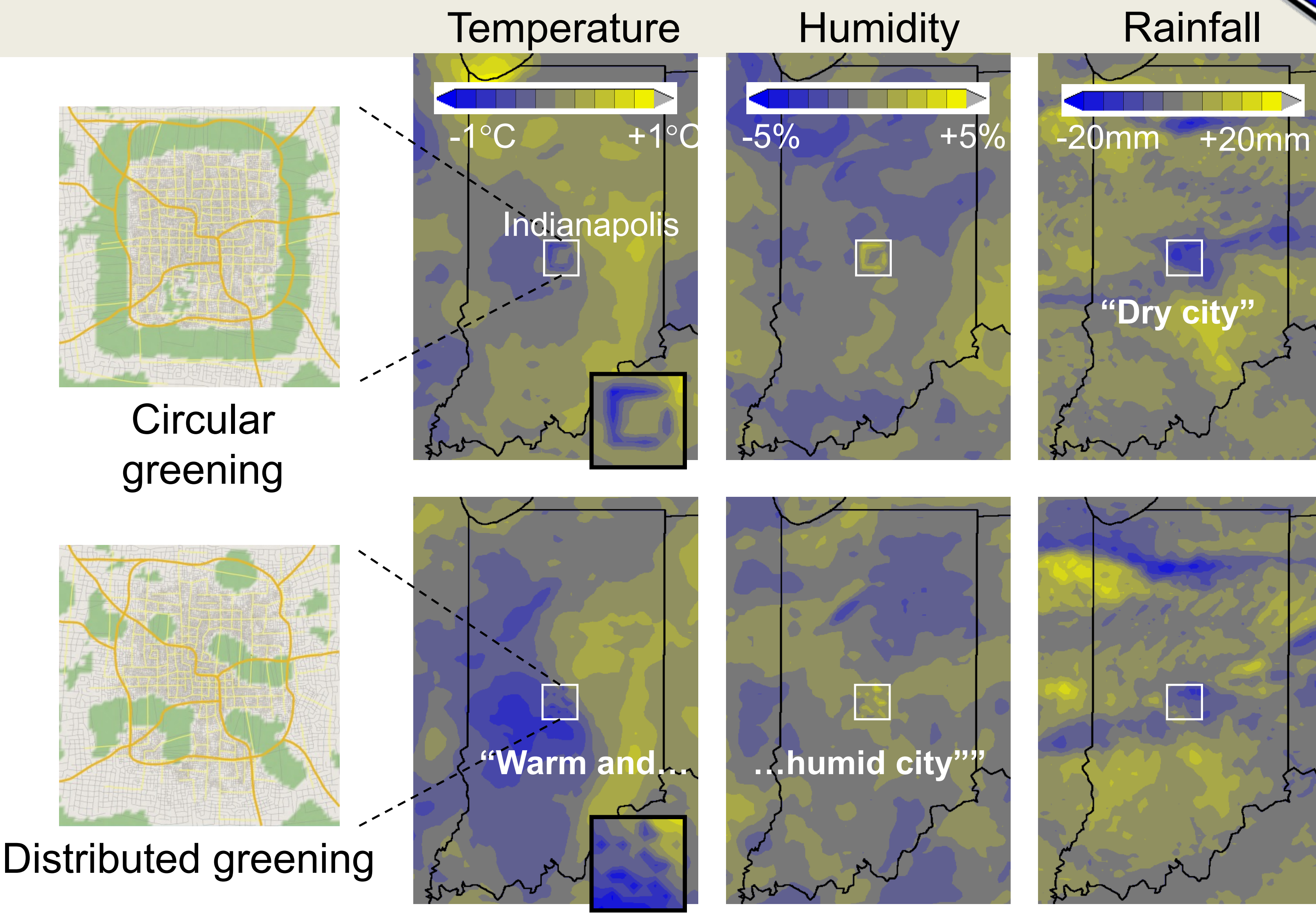
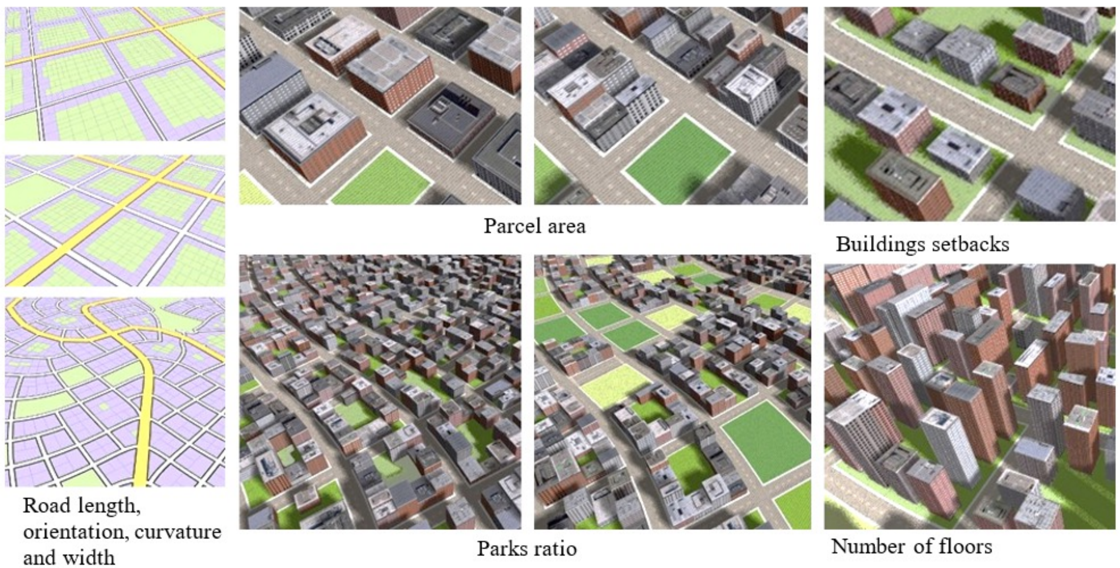


Application: Urban Flooding



[Mustafa et al. 2017/2018/2019]

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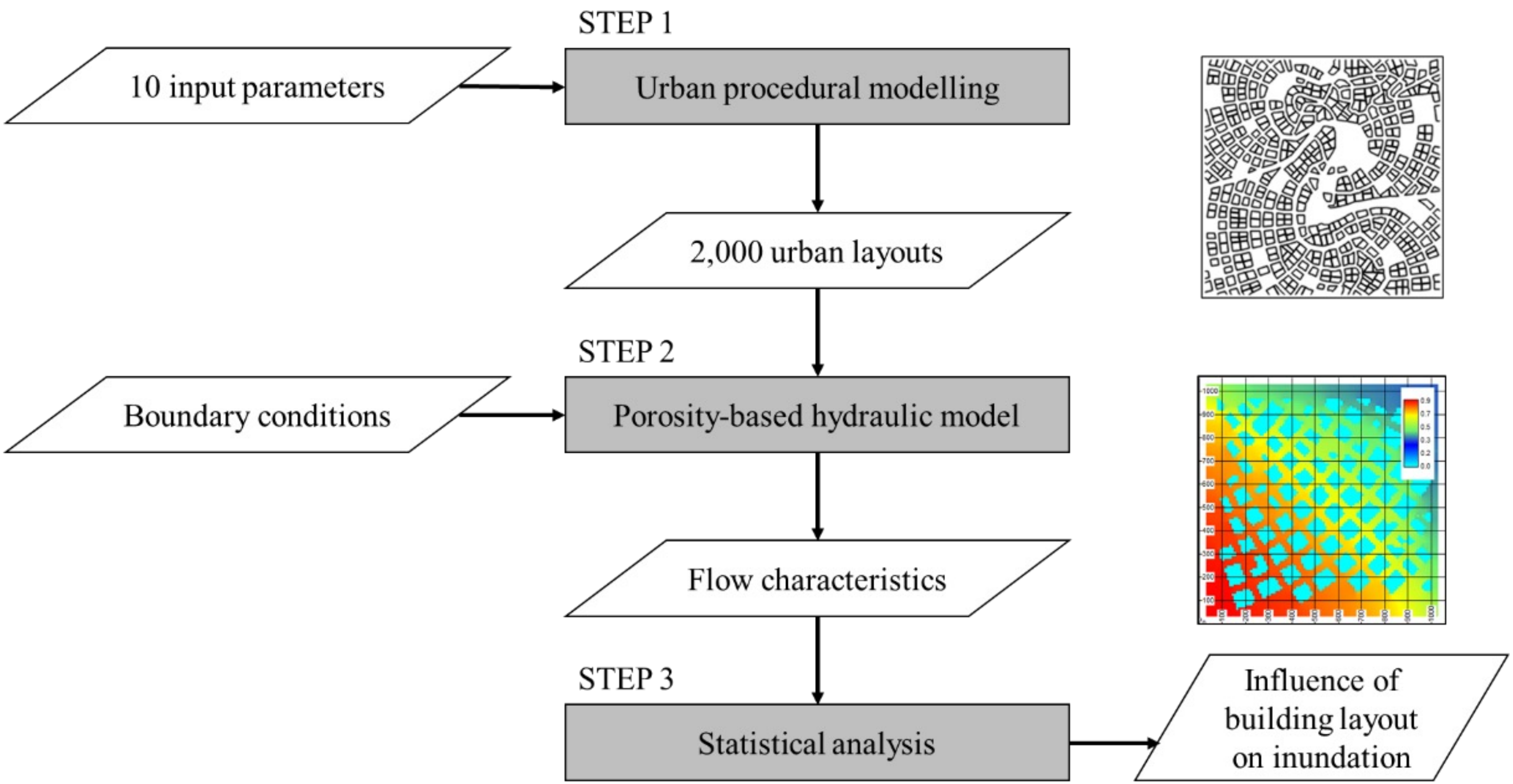

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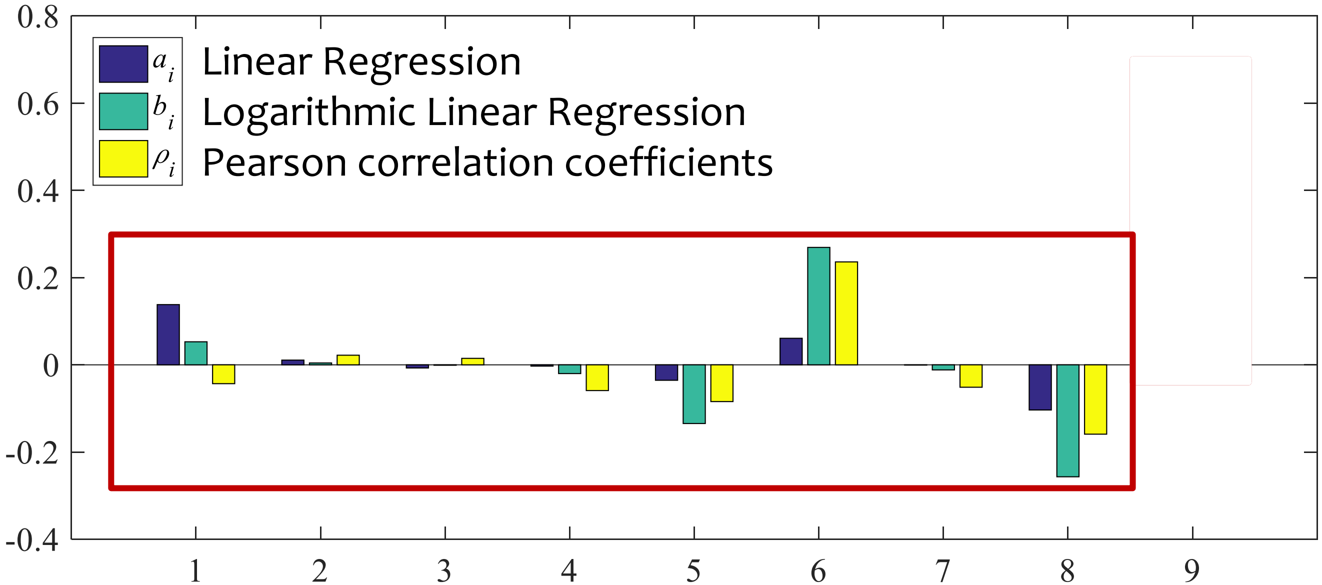

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Application: Urban Traffic

[Garcia-Dorado et al. 2014, Waddell et al. 2018]

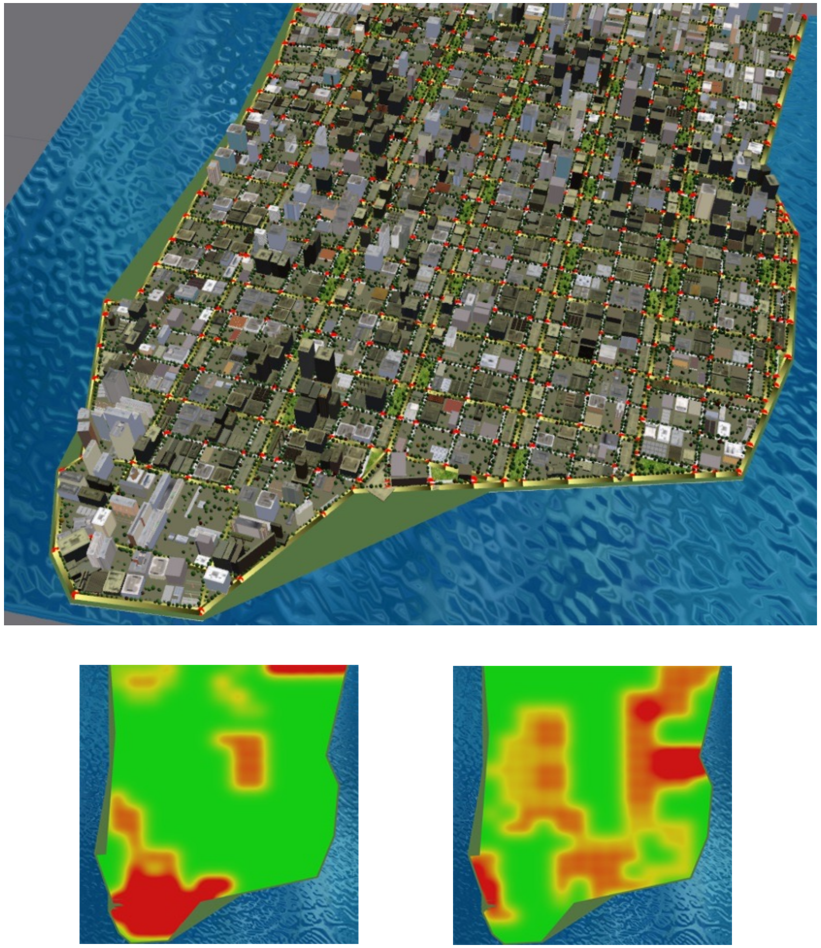
Application: Urban Traffic

Initial Simulation

Travel Time: 60min

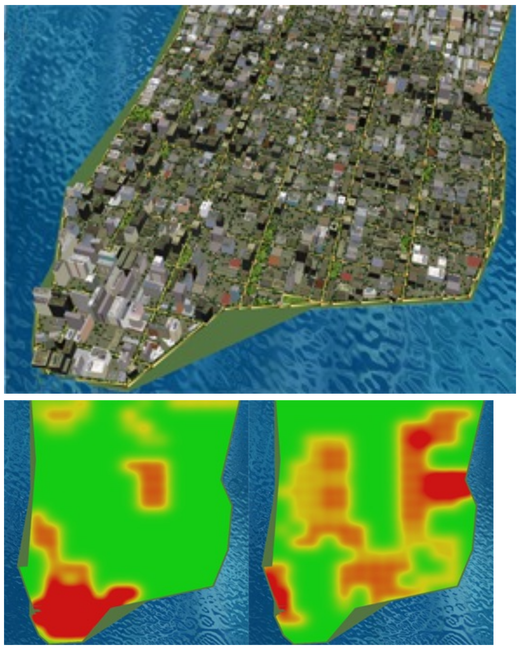
CO: 1012 gr

The user wants to optimize the city to 50, 40, and 30 min as maximum Travel Time



Application: Urban Traffic

Solutions:



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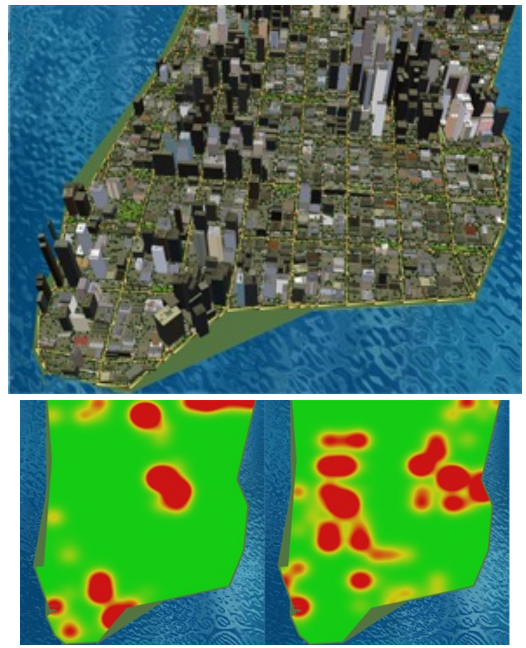

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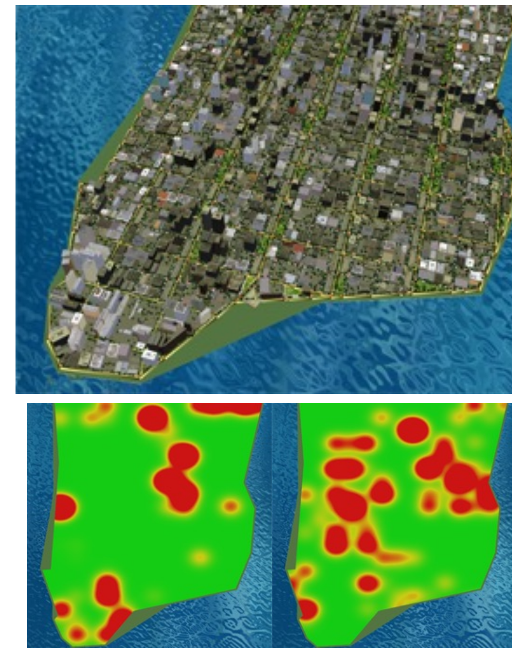

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61 Lanes

Satellite to Procedural Roofs …to Solar Planning

(a) Input urban area | (b) Initial segmentation | (c) Our footprints and roof ridges | **(d) Our procedural generation**

[Zhang et al. 2022]

www.cs.purdue.edu/homes/aliaga

Please see papers for more details!

(or ask me)

aliaga@cs.purdue.edu

Questions?

City Population

- 4000 cities with >100k population (contains roughly 30% of world population)

Cities are complex